Peer Effects on Undergraduate Business Student Performance

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Abstract

We evaluate the endogenous peer influence of students in one U.S. public University College of Business. In particular, we measure the peer effect on student grades. This study utilises an exclusion restriction approach similar to De Giorgi *et al.* (2010) to estimate the endogenous peer effect. Our results support the finding that a student's classroom performance has a significant effect on their peers. Overall, our results suggest a negative peer effect. However, we find that the direction and magnitude of the peer effect is sensitive to the student's own average ability and that of their peers.

1. Introduction

Research has shown that social interactions play an important role in influencing human behaviour. Studies on peer effects cover a wide spectrum of social contexts. For example, some analyse the role peers have on body weight (Trogdon, *et al.*, 2008), substance abuse (Kawaguchi, 2004) and academic performance (Sacerdote, 2001). Our paper focuses on the role peers have on one's academic performance. Social interactions that influence a student's ability to learn has long been of interest to researchers, policy makers, and parents. Researchers have found this question difficult to answer given the many environmental variables that can influence student performance. Even when reliable data are found there are identification issues that arise in evaluating peer effects. Manski (1993) outlines the problem of identification in the literature as the ability of researchers to separate peer effects from endogenous, exogenous or correlated effects.[1]

Recently, Lee (2007) employing a network interaction strategy shows that with groups of moderate size and sufficient size variation identification can be achieved. A number of recent papers have built on Lee's (2007) work (Bramoulle *et al.*, 2010; Boucher *et al.*, 2010) to disentangle endogenous effects from correlated effects. The use of group size variation has however been used in the literature with mixed results in determining peer effect significance (Ammermueller and Pischke, 2009; Hoxby, 2000). Recently, De Giorgi *et al.* (2010) used an exclusion restriction identification strategy that estimates indirect peer effects. The exclusion restriction approach makes use of the causal effect that one group has on another in the absence of direct contact. For example, group A may be influenced by group C, even though their members never meet, because members of A and C both meet and interact with members of group B, who serve as intermediaries of influence. Group C, whose members indirectly influence A, is known as the excluded group. De Giorgi *et al.* (2010) use a set of academic courses common to several peer groups to show that indirect peer effects influence a student's choice of college major.

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[1] See Bramoulle *et al.* (2009) and Hanushek *et al.* (2003) for an expanded discussion of the issue.

In this paper, we evaluate data from a College of Business in a State University located in the southern United States. Our analysis consists of measuring the endogenous effect that the average performance of one group of peers has on another group of students. We employ an exclusion restriction identification approach (De Giorgi *et al.*, 2010). Our estimating strategy is to evaluate the effect that one group of students has on another but where there is no shared direct interaction. In our data we identify three groups of students, groups A, B and C. One group of students (group A) has taken a course with another group of students (group B). A third group of students (group C) has taken a course with members of group B. However, group C students have never taken courses with group A. As defined earlier, group C is also referred to as the excluded group. The estimating strategy is to measure the effect that group C has on group A through group C's direct interaction with group B. We find that a group of students' grade point average (GPA) is explained by the excluded group's GPA. Our results show that the endogenous peer effects are significant and negative. The construction of our model as well as the significance of the endogenous peer effect is consistent with De Giorgi *et al.* (2010). However, the direction of the effect found is contrary to some peer effects studies (De Giorgi *et al.*, 2010; Hanushek *et al.* 2003). Nonetheless, Zimmerman (2003), Sacerdote (2001), and Henderson *et al.* (1978) show that the direction of the peer effect may be a function of the interaction between one's own ability and that of peers.

Our results show that students' ability plays an important role in explaining the magnitude and direction of the peer effect. We find that the excluded group (group C) students who are of below average ability indirectly hurt the explained group's (group A's) average GPA. However, excluded group (group C) students of above average ability pulled up the GPA of students (group A's) of above average ability. It is difficult to derive strong policy implications from these findings since in our dataset course selection is not random. However, our results suggest that diversity in a group's ability works against the academic achievement of high ability students (Kim *et al.*, 2008).

The paper is organised as follows. We first describe the existing literature, then introduce our data, outline our identification strategy and present our estimating strategy and our baseline results. We then go on to analyse the role of a group's ability and its effect on the magnitude and direction of the peer effect. The final section offers some concluding remarks.

2. Existing literature

The literature on student performance is diverse. One branch of this literature has evaluated the effect of class size on student achievement. The general hypothesis is that lower student enrolment allows for greater access to teachers. Most prior literature has shown that small class sizes positively affect student performance (Krueger, 1999; Kokkelenberg *et al.*, 2008). However, there are some studies that find no effect (for example Hoxby, 2000). Another branch of research has focused on the effects of peer performance on a student's performance (Boucher *et al.*, 2010; Black *et al.*, 2010, Ammermueller and Pischke, 2009; Kang, 2007; Hanushek *et al.*, 2003; Henderson *et al.*, 1978), or evaluates the effects of peer abilities on student achievement (Kim *et al.*, 2008; Zimmerman, 2003; Sacerdote, 2001). This paper belongs to the latter group.

Work by Kim *et al.* (2008) comparing two alternative school systems in South Korea shows that when students with similar academic abilities are assigned to the same high school (sorting) this improves the average performance of top students as compared to school systems where students are not sorted. Furthermore, they find that sorting produces a significant peer effect on top students. However, they also find that average and low ability students derive no significant benefit from sorting.

In a different context, Sacerdote (2001) using data from Dartmouth College shows that random assignment of college roommates has a significant effect on student outcomes. This present paper is closer in spirit to that of Sacerdote (2001). One difference is that we have a smaller sample from a

commuter public regional university that is less selective than Dartmouth. As in Sacerdote (2001), we use GPA as our dependent variable and use ACT (American College Testing) scores and high school GPAs as measures of innate ability. However, our findings are somewhat different. The reasons are most likely due to differences between the two populations. Our sample is more heterogeneous in respect to innate abilities, social-economic background and quality of high school. More importantly, our sample is much more restrictive. We captured students in one College of Business who have successfully completed all degree requirements. To some extent, our estimates probably understate peer effects as we were unable to measure the effect that unsuccessful peers may have on student achievement.

As outlined in Boucher *et al.* (2010) and Ammermueller and Pischke (2009), an important consideration in the literature is distinguishing between various factors of student performance. The various causes may be exogenous (influences of peers' characteristics), endogenous (resulting from interactions within the peer group) or from common influences on the peer group (correlated effects) (Manski, 1993). The literature uses various strategies to isolate these effects. The research is generally categorised by natural experiments (Boozer and Cacciola, 2001; Sacerdote, 2001; Zimmerman, 2003; Kang, 2007), quasi-experimental (Carrell *et al,.* 2009; Hoxby; 2000), fixed effects (Vigdor and Nechyba, 2004; Hanushek *et al,.* 2003) or network studies (Bramoulle *et al.*, 2010; Boucher *et al.*, 2010; De Giorgi *et al.*, 2010; Lee, 2007). This paper belongs to the latter category.

3. Data description

We collected data from a public university's College of Business located in the southern United States. All students in the sample were declared business majors who completed all coursework required for graduation. The data were originally collected to evaluate and predict student performance on the Business Major Field Test (MFT) exam administered by the Educational Testing Services (ETS). The data consist of MFT scores, undergraduate GPA, high school GPA, ACT scores and demographic information. The MFT is taken in the last semester of coursework leading to a Bachelors of Science in one of five business programmes. The MFT is embedded in the capstone course, which is offered every semester and is restricted to graduating seniors. The data consist of six semesters with MFT score information. Each student's MFT score is accompanied with two years of detailed coursework information.

Table 1A: Descriptive statistics

	Mean	SD	Min	Max
Gpa	3.01	0.57	1.3	4
act_comp	20.79	3.45	12	28
hs_gpa	3.26	0.53	1.8	4
White	0.82	0.38	0	1
Black	0.13	0.34	0	1
Female	0.52	0.50	0	1
Age	23.22	3.03	20.6	44.6
Accounting	0.32	0.47	0	1
Finance	0.11	0.31	0	1
Gen Business	0.11	0.32	0	1
Management	0.24	0.43	0	1
Marketing	0.23	0.42	0	1

We have detailed grade information on the last two years of study leading to a bachelor's degree. Table 1A has descriptive statistics of selected variables in our dataset. Table 1B provides variable definitions for those variables reported in Table 1A. Students in their last two years of study had an average GPA of 3.0. One student completed his last two years of college work with a GPA of 1.3. The average ACT

composite score is 20.8. On average, students were 23 years of age at the time they completed their course requirements leading to a bachelor's degree in business. The oldest student in the sample is 45 years of age while the youngest is 21. About 95% of the students in the sample are 26 years old or younger. The sample is composed of 52% female and 13% African American students. Roughly, 32% of all students in our sample were accounting majors, followed by management (24%). The least popular majors were finance and general business with 11% each.

Table 1B: Variable definitions

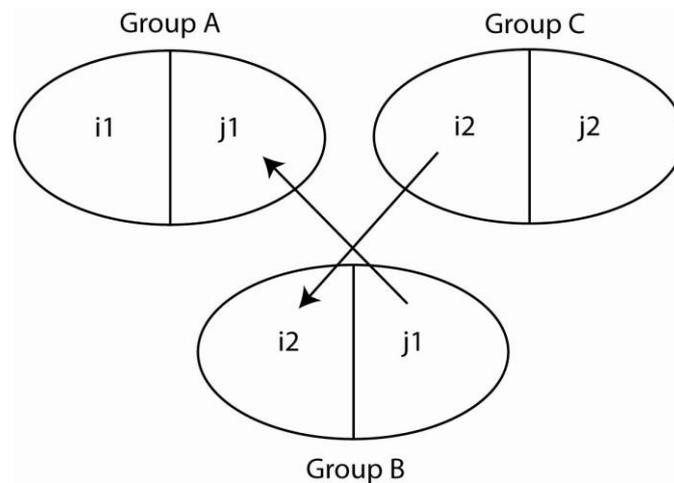| Variable name	Description
Gpa	Average GPA of student i. Last 2 years of college courses.
act_comp	ACT composite score of student i.
hs_gpa	High school GPA of student i.
White	White race dummy.
Black	African American race dummy.
Female	Female gender dummy.
Age	Age at time of MFT exam.
Accounting	Accounting major dummy.
Finance	Finance major dummy.
Gen Business	General Business major dummy.
Management	Management major dummy.
Marketing	Marketing major dummy.

4. Peer groups and identification strategy

Our dataset identifies two courses that all business students took for credit. The capstone course was taken by all business students in their last semester. The second course is a junior level Operations Management (OM) course. On average, students took the OM course one semester before their final semester. Some 29% took the OM course in their final semester. No student in our database took the OM course more than three semesters away from their last. Our dataset contains 22 OM and 15 capstone sections.

We propose an identification strategy similar to that outlined in De Giorgi *et al.* (2010). We group students based on class pairings for the OM and capstone course only. We had 322 students in our dataset that took these two courses for credit. Each student *z* chooses a course *i* and *j* to fulfil degree requirements. Let course *i* represent OM and *j* capstone courses. Each student *z* is then grouped in a pair of courses *ij*. There were 122 unique pairs of *ij* courses with an average group size of 42.5 students.

We then identified groups that had direct connections to another and all indirect groups. Because the OM course is always taken before the capstone course we paired the peer and the indirect group by course *j*. Each group had a set of peer groups and their respective group of indirect groups. Figure 1 illustrates this relationship. We generated a total of 5,069 unique three-way group pairings. Each pairing had information on the average GPA, percentage of African American, percentage of female, average high school GPA, average ACT composite score and average age of students of the two-course pair.

In Figure 1 we can observe that group A and group B share a common course. Similarly, group B and group C share a common course. However, group A and the excluded group (group C) do not share a common course. The identification strategy outlined in De Giorgi *et al.* (2010) suggests that if a peer effect exists it should be observed indirectly. That is, if group C influences group A it must be through group C's influence on group B. This is the exclusion restriction approach taken in our empirical analysis.

Figure 1: Indirect effect of excluded group on group A

The group pairings allows us to control for non-peer effects such as course date, time, instructor, etc. However, this setup may overstate the peer effect. First, we are not able to observe non-classroom interactions between group A and group C students. For example, marketing students may be members of the American Marketing Association. Secondly, some group A students may have taken other courses with group C students that we ignored in the construction of three-way pairings. Thirdly, assignment to pair courses are quite likely endogenous. Putting the limitations of our dataset aside, we believe that our overlapping interaction group and identification strategy provide a compelling case for reducing the effect of the reflective problem as outlined in the literature.

5. Estimating strategy

The strategy is as follows. There are two courses that all students take. Course *i* (Operations Management) that is taken before course *j* (capstone course). Both courses are populated by three overlapping groups of students. Group A takes course *i*1 and *j*1, group B takes course *i*2 and *j*1, and group C takes course *i*2 and *j*2. Group A and group B share the same capstone course *j*. While, group B and group C share the same Operations Management course *i*. However, no interaction takes place between group A and group C. If a peer effect exists, it should be identified indirectly. That is, if group C has an influence on group A it must be through the effect group C had on group B.

We propose the following two-stage estimating equations:

$$(1) \quad gpa_{B,j} = \beta_1 + \beta_2 gpa_{C,j} + \beta_2 X_{C,j} + u_j$$

$$(2) \quad gpa_{A,i} = \alpha_1 + \alpha_2 gpa_{B,j} + \alpha_2 X_{A,i} + u_{i,j}$$

In the first stage, we estimate the average GPA of group B instrumented by the average GPA of group C and group C specific characteristics ($X_{C,j}$). In the second stage, we estimate the average GPA of group A with the fitted GPA of group B and group A's specific controls ($X_{A,i}$). If a peer effect exits, then α_2 should be significantly different from zero.

6. Results

From equations (1) and (2) we produce the regression results reported in Table 2. We show in Column (1) the OLS specification for comparison purposes. The OLS results show that the average GPA of peers has a significant positive effect on group A. Columns (2) and (3) are our 2SLS specifications. Column (3) uses group C's GPA as an instrument for group B's GPA. Column (3) includes the full set of instruments.

Recall that the 2SLS specification tests whether group C influences group A through group C's effect on group B. Columns (2) and (3) show that group C's influence on group B lead to a negative effect on group A's GPA. We discuss the reason for the negative sign in the next section. However, it is important to point out that the effect is significant. That is, our exclusion restriction method supports the existence of a peer effect. In column (3) specification, group B's GPA is estimated (equation (1)) by group C's GPA and group C's specific characteristics. This lowers the magnitude of the effect only slightly. To evaluate the magnitude of peer effect we standardise our estimate as in Ammermueller and Pishke (2009). We multiply the first stage fitted variance of the peer group by the peer coefficient and divide it by the variance of group A's GPA. This procures an effect of -0.09. This suggest that a 1 standard deviation increase in the fitted peer groups GPA lowers group A's GPA by 0.09 standard deviations, where the mean GPA of group A is 2.89 and its variance is 0.02.

Table 2: Peer effect on group performance

Dependent variable: Group A's average GPA	OLS (1)	2SLS (2)	2SLS (3)
Peer effect: Group B's GPA	0.292*** (0.014)	−0.218*** (0.031)	−0.199*** (0.027)
Group A's characteristics			
Percentage African American	−0.307*** (0.033)	−0.289*** (0.037)	−0.290*** (0.037)
Percentage female	0.439*** (0.023)	0.683*** (0.029)	0.674*** (0.028)
Average high school GPA	−0.177*** (0.028)	−0.471*** (0.035)	−0.461*** (0.033)
Average age	0.020*** (0.003)	0.030*** (0.003)	0.030*** (0.003)
Average ACT composite score	0.025*** (0.004)	0.042*** (0.005)	0.041*** (0.005)
Constant	1.407*** (0.143)	3.130*** (0.185)	3.066*** (0.176)
Observations	5069	5069	5069
R-sq	0.269	–	–
Shea partial R^2	–	0.254	0.336
First stage F-test	–	1646.8	425.11

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (standard errors in parentheses).

Group A's specific controls produce coefficients that are consistent with existing literature. Groups that are associated with a larger share of African Americans tend to achieve a lower GPA. Groups composed of a larger share of female students achieve higher GPAs. Here we find that higher group high school GPAs lead to a lower average GPA. However, this is offset by the average composite ACT score of the group that has a positive effect on average GPA. Lastly, groups composed of older students on average will have higher GPAs.

7. Excluded group ability

In this section we test the robustness of our results by the type of excluded group (group C's) ability level. We used the specification of Table 2 column (3) as our comparison estimation results. We take the average ability of the excluded group (group C) and break it into four categories (bottom 25th percentile, bottom half, top half, and top 75th percentile). We produce estimated results of these categories in Table 3. Column (1) shows the effect of the excluded group students (group C) from the bottom 25th percentile of the ability spectrum, on group A students. Column (2) shows the effects of group C students from the bottom 50th percentile of ability, on group A students. Both columns (1) and (2) show that low ability excluded group students (group C) have a negative effect on group A's GPA. The effect, while negative, is not significant for high ability excluded group (group C) students (columns (3) and (4)).

The results reported in Table 3 suggest that the negative effect found on our baseline estimation is probably driven by low ability excluded group (group C) students. Columns (1) and (2) peer effect is also a larger negative number than our baseline model. This suggests that low ability excluded group (group C) students drive most of the negative peer effect on group A students.

Next, we further partition our data to evaluate the effect of the excluded group's (group C) ability by groups A's ability level. Again, we take the average ACT composite score of group A as the measure of ability. Table 4 columns (1) and (2) show the bottom half ability of the excluded group (group C) on the bottom half (column (1)) and top half ability group A students (column (2)). Columns (1) and (2) clearly show that low ability excluded group (group C) students pull down both low ability and high ability group A students. However, the magnitude of the negative effect is larger on higher ability group A students.

Table 3: Peer effects on group performance – by excluded group ability levels

	Excluded group ability			
	< 25th Percentile	Bottom half	Top half	> 75th percentile
Dependent variable:	2SLS	2SLS	2SLS	2SLS
Group A's average GPA	(1)	(2)	(3)	(4)
Peer effect:	−0.210***	−0.215***	−0.020	−0.010
Group B's GPA	(0.044)	(0.029)	(0.043)	(0.060)
Group A's characteristics				
Percentage African	−0.077	−0.207***	−0.361***	−0.321***
American	(0.079)	(0.051)	(0.050)	(0.065)
Percentage female	0.751***	0.717***	0.525***	0.511***
	(0.048)	(0.034)	(0.044)	(0.061)
Average high school	−0.442***	−0.443***	−0.382***	−0.433***
GPA	(0.067)	(0.045)	(0.047)	(0.061)
Average age	0.015***	0.027***	0.029***	0.033***
	(0.006)	(0.004)	(0.004)	(0.005)
Average ACT	0.047***	0.043***	0.034***	0.031***
composite score	(0.010)	(0.007)	(0.007)	(0.008)
Constant	3.199***	3.044***	2.549***	2.645***
	(0.350)	(0.230)	(0.254)	(0.345)
Observations	1313	2845	2224	1301
Shea partial R^2	0.493	0.45	0.277	0.277
First stage F-test	210.66	386.74	141.29	82.12

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (Standard errors in parentheses).

Columns (3) and (4) consider the effect of the group C students from the top half of the ability spectrum on group A students from the bottom (column (3)) and top (column (4)) halves of the ability spectrum. Column (3) shows that top half ability excluded group (group C) students pull down bottom half group A students. This result is hard to reconcile. One possible explanation may be that high ability group C students discourage middle to low ability group B students who in turn discourage low ability group A students. Column (4) shows that high ability excluded group (group C) students indirectly influence high ability group A students in a positive way. This effect is of the same magnitude as that found in column (2), albeit of different signs.

Table 4: Peer effect on group performance – by excluded group and group A's ability levels

Dependent variable: Group A's average GPA	Excluded group and group A's ability			
	Group C: bottom half ability		Group C: top half ability	
	Group A: bottom half ability	Group A: top half ability	Group A: bottom half ability	Group A: top half ability
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Peer effect: Group B's GPA	−0.099***	−0.343***	−0.224***	0.334***
	(0.032)	(0.051)	(0.062)	(0.045)
Group A's characteristics				
Percentage African American	−0.466***	0.548***	−0.646***	0.198***
	(0.072)	(0.090)	(0.078)	(0.074)
Percentage female	0.444***	1.058***	0.408***	0.451***
	(0.043)	(0.057)	(0.056)	(0.058)
Average high school GPA	−0.517***	−0.543***	−0.646***	−0.272***
	(0.059)	(0.071)	(0.075)	(0.056)
Average age	0.068***	0.044***	0.071***	0.050***
	(0.014)	(0.014)	(0.016)	(0.012)
Average ACT composite score	−0.021***	0.086***	−0.016***	0.056***
	(0.005)	(0.006)	(0.006)	(0.005)
Constant	3.841***	1.993***	4.504***	0.109
	(0.347)	(0.405)	(0.420)	(0.318)
Observations	1554	1291	1241	983
Shea partial R^2	0.552	0.391	0.283	0.386
First stage F-test	316.75	136.95	80.95	101.7

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (Standard errors in parentheses)

8. Conclusion

In this paper, we evaluated peer effects using an exclusion restriction identification approach similar to that employed by De Giorgi *et al.* (2010). Results of this research indicate that student influence on peers takes place in the absence of direct contact in a common course. Additionally, in this specific setting, our results suggest that the excluded group (group C) affects students indirectly in a negative way. The negative effect is primarily driven by the ability type of student groups. Low ability excluded group (group C) students had a negative indirect effect on other students. While, high ability excluded group (group C) students had a negative impact on low ability students. Finally, high ability excluded group (group C) students had a positive influence on other high ability students. Results suggest that endogenous peer effects are significant and negative for students with low academic aptitude relative to peers. However, we found no significant peer effect for high ability students (group A) among low

ability peers. Our results support existing literature that find that peer group performance has a significant effect on student academic achievement.

It is difficult to draw policy implications from these types of studies. In particular, work by Manski (1993) and more recently Bramoulle *et al.* (2009) have shown that parsing out the effects of groups on individuals is a challenging task. Nonetheless, the present study suggests that there is an intimidation factor present whenever low ability students are among high ability students. It suggests that classroom diversity may not be an appropriate tool to draw positive GPA externalities from social interactions. These results support a sorting strategy as found in Kim *et al.* (2008).

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